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VOLTAGE-CONTROL BASED ON FUZZY ADAPTIVE PARTICLE SWARM OPTIMIZATION TECHNIQUE

Assad Abu-Jasser[1], Husam Shaheen[2]

[1]Electrical Engineering Department, The Islamic University Of Gaza
Email: ajasser@iugaza.edu.ps
[2]Engineering and Maintenance Administration, Ministry of Health - Gaza
Email: husam3523@yahoo.com

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تعتبر المحافظة علي الجهد الكهربائي عند مستوي مقبول في شبكات النقل وخطوط التوزيع من أكبر التحديات والمهام. وتصنفعملية التحكم في الجهد الكهربائي من ضمن المشاكلغيرالخطية وتعتمد بشكل أساسي على توزيع ومرور القدرة فى شبكات النقل, وبالرغم من وجود عدة طرق مختلفة للتحكم بالجهد الكهربائي إلا أن النظم الكهربية حول العالم تتعرض لمشاكل ذات علاقة بعدم إستقرار الجهد وفي بعض الحالات ينتج إنهيار كامل للنظام.هناك عدة طرق جديدة للتحكم في الجهد الكهربائي تعتمد علي البرمجة العشوائية المتطورة والتي أثبتت نجاعتها علي الطرق التقليدية. في هذه الورقة سيتم عرض طريقة جديدة للتحكم بالجهد وهتجمع بين أنظمة التحكم الضبابي المنطقي والبرمجة المتطورة Adaptive Particle Swarm Optimization حيث أن التحكم الضبابي المنطقي يستخدم فى تعديل معاملات البرمجة المتطورة.

Keeping an acceptable voltage profile at the system buses is a local and a system-wide challenging task. The power flow in the system transmission lines dictates the voltage profile at the system buses. Voltage-control is nonlinear problem and rooted dominantly in rescheduling of the reactive power flow at a certain loading condition. Despite the fact that a number of voltage-control techniques are available to electric power system operators, these systems around the world have been subjected to voltage instability problems and in some cases to voltage collapses that cause complete system breakdowns. Several stochastic techniques or a combination of these techniques have been recently introduced to handle the voltage control problem and these techniques have proven to be superior over traditional techniques. This paper introduces a new stochastic voltage–control methodology based on a combination of fuzzy-logic and adaptive particle swarm optimization. The fuzzy logic is used to adapt parameters of theadaptive particle swarm optimization.

Keywords: Voltage profile, voltage collapse, stochastic techniques, fuzzy-logic, and adaptive particle swarm optimization

1. INTRODUCTION

It is of great importance to keep the voltage profile at power system buses within a prescribed tolerance because all present day equipments which utilize electric power such as lights; motors, thermal appliances, and electronic appliances are designed for use within a certain definite terminal voltage, the nameplate voltage. If the voltage deviates from this value, the efficiency, life expectancy, and the quality of performance of the equipment will suffer. Some electrical equipment are more sensitive to voltage variation than others such as motors. However, it is not economically possible to maintain voltage absolutely constant at every consumer's service terminals [1]. This means that the variations in voltage are permissible, but with favorable zones, for example the rise or drop in voltage should not exceed a prescribed tolerance of the nominal voltage. Although a large spectrum of optimization problems has grown in size and complexity [2], the solution to complex multidimensional problems by means of classical optimization techniques is extremely difficult [3,4] and computational expensive. In general, heuristic algorithms which are referred to as "stochastic" optimization techniques have facilitated solving optimization problems that were previously very difficult or impossible to solve [5]. These tools include: genetic algorithms, evolutionary strategies, evolutionary programming, simulated annealing, and particle swarm optimization.

Particle Swarm Optimization, [6, 7] PSO refers to a relatively new family of algorithms that based on iterative process and may be used to find optimal or near optimal solutions to numerical and qualitative problems. Particle Swarm Optimization was introduced by Russell Eberhart and James Kennedy in 1995 [8], inspired by social behavior of bird flocking or fish schooling using PSO technique. In recent years a lot of papers were published in the power system Applications [9, 10]. H. Yoshida et al. [11] proposed a Particle Swarm Optimization PSO for reactive power and Voltage-VAR Control VVC. It determines an on-line VVC strategy with continuous and discrete control variables such as automatic voltage regulator AVR, tap positions of online tap changing transformers and a number of reactive power compensation equipment. The APSO algorithm has three parameters called inertia weight (*w*), cognitive parameter (c_1), and social parameter (c_2). In adaptive particle swarm, the inertia weight (*w*) is modified according to linearly decreased equation while the social and cognitive parameters remain constant during the iteration process according to Cui-Ru Wang et al. [12]. Wen Zhang and Yutian Liu [13] presented FPSO. In the FPSO, the fuzzy system was used to modify all of the parameter of particle swarm optimization.

This paper introduces a new technique that combines Fuzzy-logic and APSO which will be abbreviated as FAPSO [14]. In this method, the inertia weight of the APSO will be adjusted separately according to a certain linear function while the social and cognitive parameters will be modified using the fuzzy logic. The main objective of this work is to employ this modern heuristic optimization algorithm FAPSO to solve the voltage-control problem in order to enhance voltage stability through rescheduling of the reactive power generation and flow in the system transmission lines [15]. Various tools such as capacitor banks, tap-changing-transformers, and voltage-controlled buses will be employed. In the same time an economic dispatch of the power generation to reduce the generation cost and to minimize the real power loss will be sought. In addition, the voltage deviation and the real power loss will be minimized.

2. Research Methodology

In order to demonstrate the validity of the proposed technique: it is suggested to select an appropriate power system model, to develop a mathematical model for the selected system using the proposed technique, and finally to apply the mathematical model to the selected system to obtain a solution to the voltage-control problem while satisfying a number of constraints. The following summarizes these procedures and steps:

1. Selecting a system model that has an appropriate number of buses and includes a variety of voltage-control tools such as tap-changing transformers and capacitor banks.
2. Formulating the voltage-control, the voltage deviation and the real power loss as mathematical optimization problems using the suggested control technique subject to the applicable constraints.
3. Applying the Fuzzy Adaptive Particle Swarm Optimization mathematical model to the problems addressed using Matlab code.
4. Tabulating and examining of the obtained results to check whether the system voltage profile is acceptable and at the same time all constraints are met. The results obtained will be also compared with that of the traditional optimal economic dispatch as a reference optimization technique.

3. Power System Model Description

The standard IEEE 30-bus system is chosen as a test system to examine the validity of the new technique [16]. The IEEE 30-bus system is proposed as a model system in order to examine and validate the new approach. The following Figure and tables show the system topology and data:

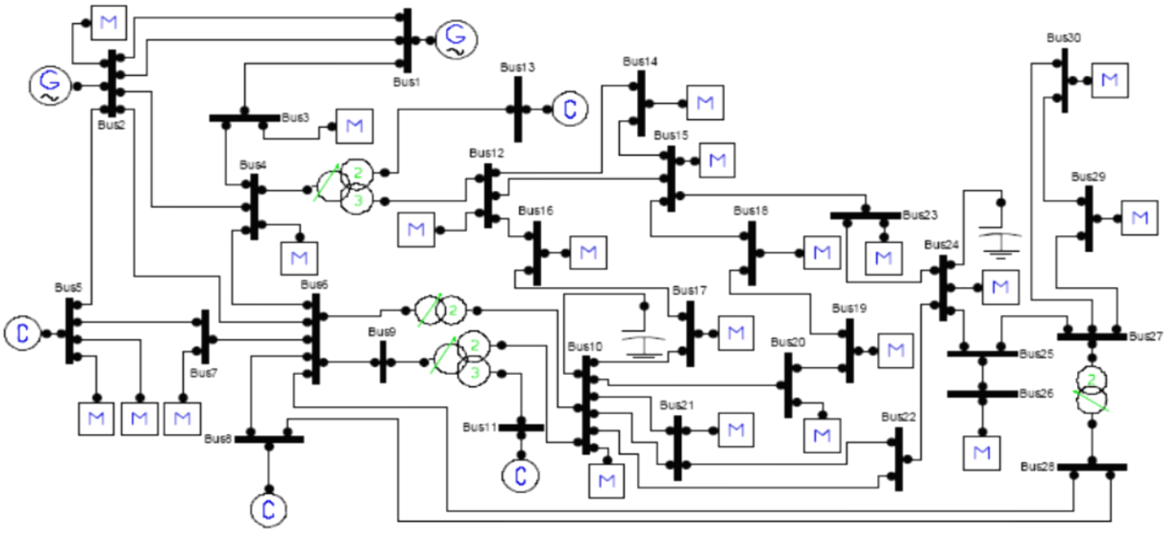

Figure 1. The IEEE 30-Bus system model

The system consists of thirty buses, bus number one is assigned as slack bus, while buses 2, 5, 8, 11, and 13 are taken as voltage controlled buses, and the remaining are load buses. Four tap changer transformers are also available: the first transformer between bus number 6 and bus number 9, the second between bus number 6 and bus number 10, the third between bus number 4 and bus number 12, and the last transformer between bus number 28 and bus number 27. All tap settings of the four transformers are used as control variable. There are also two capacitor banks connected to buses 10 and 24.

Table 1: Bus data of IEEE 30-Bus system model

Bus data		**Voltage**	**Angle**	**Load**		**Generation**				**Static Mvar**
No	**Code**	**pu**	**Degree**	**MW**	**Mvar**	**MW**	**Mvar**	**Qmin**	**Qmax**	**+Qc/Ql**
1	1	1.05	0	0	0	0	0	0	0	0
2	2	1.05	0	21.70	12.7	40	0.0	-40	50	0
3	0	1.0	0	2.4	1.2	0	0	0	0	0
4	0	1.0	0	7.6	1.6	0	0	0	0	0
5	2	1.05	0	94.2	19.0	0	0	-40	60	0
6	0	1.0	0	0	0.0	0	0	0	0	0
7	0	1.0	0	22.8	10.9	0	0	0	0	0
8	2	1.05	0	30	30.0	0	0	-30	70	0
9	0	1	0	0	0	0	0	0	0	0
10	0	1	0	5.8	2	0	0	0	0	10
11	2	1.05	0	0	0	0	0	-6	24	0
12	0	1.0	0	11.2	7.5	0	0	0	0	0
13	2	1.05	0	0	0	0	0	-6	40	0
14	0	1	0	6.2	1.6	0	0	0	0	0
15	0	1	0	8.2	2.5	0	0	0	0	0
16	0	1	0	3.5	1.8	0	0	0	0	0
17	0	1	0	9.0	5.8	0	0	0	0	0
18	0	1	0	3.2	0.9	0	0	0	0	0
19	0	1	0	9.5	3.4	0	0	0	0	0
20	0	1	0	2.2	0.7	0	0	0	0	0
21	0	1	0	17.5	11.2	0	0	0	0	0
22	0	1	0	0	0	0	0	0	0	0
23	0	1	0	3.2	1.6	0	0	0	0	0
24	0	1	0	8.7	6.7	0	0	0	0	4.3
25	0	1	0	0	0	0	0	0	0	0
26	0	1	0	3.5	2.3	0	0	0	0	0
27	0	1	0	0	0	0	0	0	0	0
28	0	1	0	0	0	0	0	0	0	0
29	0	1	0	2.4	0.9	0	0	0	0	0
30	0	1	0	10.6	1.9	0	0	0	0	0

Table 1 contains the bus data, column two for the bus type: code 0: represents a load bus, code 1: represents a slack bus and code 2: represents a voltage controlled bus. Column 3 and column 4 present the voltage magnitude and phase angle in degrees respectively, while column 5 and column 6 describe the power load demand. Also column 7, column 8, column 9, and column 10 represent the power generations and their minimum and maximum limits. Finally column 11 states the capacitor bank size connected to the respective bus. Table 2 contains the line data, column 1 and column 2 are reserved for line bus number, column 3, column 4 and column 5 are used for line resistance, reactance and one half of total line charging susceptance, and column 6 has the value of 1 for transmission line or transformer tap setting.

Table 2: Line Data of the IEEE 30-Bus System Model

From Bus	To Bus	Type	R pu	X pu	½ B pu	Line code=1for lines>1 or <1 for Transformer Tap
1	2	T L	0.0192	0.0575	0.02640	1
1	3	T L	0.0452	0.1852	0.02040	1
2	4	T L	0.0570	0.1737	0.01840	1
3	4	T L	0.0132	0.0379	0.00420	1
2	5	T L	0.0472	0.1983	0.02090	1
2	6	T L	0.0581	0.1763	0.01870	1
4	6	T L	0.0119	0.0414	0.00450	1
5	7	T L	0.0460	0.1160	0.01020	1
6	7	T L	0.0267	0.0820	0.00850	1
6	8	T L	0.0120	0.0420	0.00450	1
6	9	Transformer	0	0.2080	0	0.978
6	10	Transformer	0	0.5560	0	0.969
9	11	T L	0	0.2080	0	1
9	10	T L	0	0.1100	0	1
4	12	Transformer	0	0.2560	0	0.932
12	13	T L	0	0.1400	0	1
12	14	T L	0.1231	0.2559	0	1
12	15	T L	0.0662	0.1304	0	1
12	16	T L	0.0945	0.1987	0	1
14	15	T L	0.2210	0.1997	0	1
16	17	T L	0.0824	0.1923	0	1
15	18	T L	0.1073	0.2185	0	1
18	19	T L	0.0639	0.1292	0	1
19	20	T L	0.0340	0.0680	0	1
10	20	T L	0.0936	0.2090	0	1
10	17	T L	0.0324	0.0845	0	1
10	21	T L	0.0348	0.0749	0	1
10	22	T L	0.0727	0.1499	0	1
21	22	T L	0.0116	0.0236	0	1
15	23	T L	0.1000	0.2020	0	1
22	24	T L	0.1150	0.1790	0	1
23	24	T L	0.1320	0.2700	0	1
24	25	T L	0.1885	0.3292	0	1
25	26	T L	0.2544	0.3800	0	1
25	27	T L	0.1093	0.2087	0	1
28	27	Transformer	0	0.3960	0	0.968
27	29	T L	0.2198	0.4153	0	1
27	30	T L	0.3202	0.6027	0	1
29	30	T L	0.2399	0.4533	0	1
8	28	T L	0.0636	0.2000	0	1
6	28	T L	0.0169	0.0599	0	1

TL is a transmission line

The objective function of voltage-control problem comprises three important terms, which are: maintaining acceptable system voltage profile, minimizing the voltage deviation at the load buses, and minimizing the real power loss in the transmission grid. It is of great importance to maintain the voltage at all buses in an acceptable range between 0.95 and 1.05 pu. Bus voltage is one of the most important securities and service quality, one of the effective ways to avoid the voltages from moving toward their maximum or minimum limits after optimization, is to choose the deviation of voltage from the desired value as an objective function, that is:

$$\min f_1 = \sum_{i=1}^{N_L} \frac{|v_i - v_i^*|}{N_L} \tag{1}$$

Where f_1 is the per unit average voltage deviation, N_L is the total number of the system load buses, v_i and v_i^* are the actual voltage magnitude and the desired voltage magnitude at bus$i$. Minimizing the total real power loss can be expressed as follows:

$$\min f_2 = P_{loss}(x, u) \tag{2}$$

Where f_2 is the total active power losses of the power system, $x$is the state variable vector consisting of load bus voltages $V_L$and generator reactive power outputsQ_G , $u$is the control variable vector consisting of generator voltages, $V_G$shunt VAR compensations $Q_c$and transformer tap settings$T$.

On the other hands, the mathematical formulation can be expressed as follow:

$$\min f_2 = \min\left\{\sum_{i=1}^{N}\sum_{j=1}^{N}\left[g_{ij} \times \left(|V_i|^2 + |V_j|^2 - 2 \times |V_i| \times |V_j| \times cos(\delta_i - \delta_j)\right)\right]\right. \tag{3}$$

Where,

N : Number of buses

$|V_i|$: Voltage magnitude at bus i

$|V_j|$: Voltage magnitude at bus j

g_{ij} : Conductance of transmission line between bus i and bus j

δ_i : Voltage angle at bus i

δ_j : Voltage angle at bus j

The following constraints are known as the power balance constraints. They guarantee that the load demand will be met considering the transmission losses of the system. These constraints are the main objective in a power flow analysis.

$$\sum P_G - \sum P_D - P_L = 0 \tag{4}$$

$$\sum Q_G - \sum Q_D - Q_L = 0 \tag{5}$$

Where,

P_G : Real power generation

P_D : Real power demand

P_L : Real power loss

Q_G : Reactive power generation

Q_D : Reactive power demand

Q_L : Reactive power loss

The operational constraints guarantee a safe operation of the system. The capacity limits should be met at all time to avoid damage to power system components and maintain system stability. The following constraints state real and reactive power generation limits for each generation unit:

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \tag{6}$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \tag{7}$$

Where,

P_{Gi}^{min} : Lower real power generation limit of unit i

P_{Gi}^{max} : Upper real power generation limit of unit i

Q_{Gi}^{min} : Lower reactive power generation limit of unit$i$

Q_{Gi}^{max} : Upper reactive power generation limit of unit i

In order to maintain system stability, the voltage at each bus should be within its limits. The following constrain shows this operational condition:

$$V_i^{min} \le |V_i| \le V_i^{max} \tag{8}$$

Where:

V_i^{min} : Lower voltage magnitude limit at bus i

V_i^{max} : Upper voltage magnitude limit at bus i

The optimal voltage-control and reactive power dispatch can be achieved by employing reactive power compensator devices such as shunt capacitor banks, and by adjusting the transformer tap positions. Shunt capacitor banks and transformer tap positions are control variables for the voltage-control problem [10]. The operational limits of these devices are expressed in the following constrains:

$$Q_C^{min} \le Q_C \le Q_C^{max} \tag{9}$$

$$\mathrm{T_k^{min}} \le \mathrm{T_k} \le \mathrm{T_K^{max}} \tag{10}$$

Where:

Q_C : Reactive power generated by the shunt capacitor bank C

Q_C^{min} : Lower limit of shunt capacitor bank C

Q_C^{max} : Upper limit of shunt capacitor bank C

T_k : Tap position of transformer k

T_k^{min} : Lower tap position limit of transformer k

T_k^{max} : Upper tap position limit of transformer k

The transformer tap settings and the adjustable shunt capacitor banks are the essential key elements in transmission loss reduction. In power systems, almost all transformers provide taps on windings to adjust the ratio of transformation, also have adjustable shunt capacitor banks located in specified buses in order to correct voltage and power factor problems. In a mathematical formulation, the transformers tap settings and the adjustable shunt capacitor banks may be represented either as continuous or discrete variables, depending on the study issued. In this work, the transformers tap settings and the adjustable shunt capacitor banks are considered as continuous variables.

Variables values were forced to be within their limits. Any parameter that violates the limits is replaced with values using equation 11:

$$u_i = \begin{cases} u_i^{min} if u_i < u_i^{min} \\ u_i^{max} if u_i > u_i^{max} \\ u_i otherwise \end{cases} \quad (11)$$

Where: u_i is any parameter variable

4. Fuzzy Adaptive Particle Swarm Optimization Algorithm

The control variables for voltage-control problem which will be modified by the particle swarm optimization process are: the voltage magnitude at the slack bus, the voltage-controlled buses, transformers' tap settings, and adjustable shunt capacitor banks. There are twelve control variables for the IEEE 30-Bus system. The first position of control variables vector is the slack bus. The next five position for the five voltage magnitudes at the voltage-controlled buses (PV-buses). The next four positions of the control variables vector are the transformers tap settings. The transformer tap settings are considered as continuous variables, they are adjusted in the range [0.9-1.1]. The last two positions of the control variables vector are the adjustable shunt capacitor banks. These variables are also considered as continuous variables, they are adjusted in the range [0-10 MVAR]. All control variables were handled using the Particle Swarm Optimization and fuzzy system model for continuous variables. The following table shows the control variables vector.

Table 3. System Control Variables

Control Variables Vector or Particle											
1	2	3	4	5	6	7	8	9	10	11	12
V_1	V_2	V_5	V_8	V_{11}	V_{13}	T_{6-9}	T_{6-10}	T_{4-12}	T_{28-27}	Q_{10}	Q_{24}

At each iteration, every particle determines a possible set of values for voltage magnitudes at PV buses, transformers tap positions and total capacity of each shunt capacitor bank. Subsequently, they are used to run a power flow, calculate the transmission losses, voltage deviation and evaluate the fitness function. The particle swarm optimization contains three tuning parameters w, c_1 and c_2 as shown in equations 12 and 13 that influences the algorithm performance, often stated as the exploration–exploitation tradeoff. Exploration is the ability to test various regions in the problem space in order to locate a good optimum, the global one. Exploitation is the ability to concentrate the search around a promising candidate solution in order to locate the optimum precisely. The inertia weight w is employed to control the impact of the previous history of velocities on the current velocity.

$$v_i^{k+1} = w \times v_i^k + c_1 \times rand(\quad)_1 \times \left(pbest_i - s_i^k\right) + c_2 \times rand(\quad)_2 \times \left(gbest - s_i^k\right) \quad (12)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (13)$$

Where,

v_i^{k+1} : $velocity of particle i at iteration k+1$

v_i^k : $velocity of particle i at iteration k$

S_i^{k+1} : $position of particle i at iteration k+1$

s_i^k : $position of particle i at iteration k$

w: inertia weight

c_1 : $constant weighting factor related to pbest$

c_2 : $constant weighting factor related to gbest$

$\mathrm{rand}()_1$: $random\ number\ between$ 0 and 1

$\mathrm{rand}()_2$: $random\ number\ between$ 0 and 1

$pbest_i$: $pbest position of particle i$

$gbest$: $gbest position of swarm$

Expressions in equations 12 and 13, describe the velocity and position update, respectively [13]. The expression in equation 12 calculates a new velocity for each particle based on the particle's previous velocity, the particle's location at which the best fitness has been achieved so far, and the population global location at which the best fitness has been achieved so far. In addition, c_1 and c_2 are positive constants called the cognitive parameter and the social parameter, respectively. These constants provide the correct balance between exploration and exploitation (individuality and sociality). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward p-best and g-best locations. The random numbers provide a stochastic characteristic for the particles velocities in order to simulate the real behavior of the birds in a flock. An inertia weight parameter w was introduced in order to improve the performance of the original Particle Swarm Optimization model. This parameter plays the role of balancing the global search and local search capability of Particle Swarm Optimization. It can be a positive constant or even a positive linear or nonlinear function of time.

A larger inertia weight *w* facilitates global exploration while a smaller inertia weight tends to facilitate local exploration to fine-tune the current search area. Suitable selection of the inertia weight *w* can provide a balance between global and local exploration abilities, thus require less iterations on average to find the optimum. The learning factors c_1 and c_2 determine the influence of personal best p-best and global best g-best. Since c_1 expresses how much the particle trusts its own past experience, it is called cognitive parameter. While c_2 expresses how much it trusts the swarm, it is called social parameter. In addition the PSO is influenced by the number of particles and the swarm size N, in the swarm. Since the parameters of PSO are influenced and deeply affect the algorithm performance, we concentrate in this paper on these parameters.

This new control method combined both fuzzy system [17] and adaptive particle swarm optimization. A fuzzy adaptive particle swarm optimization (FAPSO) will be proposed to improve the performance of PSO where the inertia weight was modified according to linearly decreased equation 14, while c_1 and c_2 are modified according to fuzzy logic [18].

$$w = \mathrm{w}_{\max} - \left(\frac{\mathrm{w}_{\max} - \mathrm{w}_{\min}}{\mathrm{iter}_{\max}}\right) \times iter \tag{14}$$

Where:

$iter_{max}$: maximum number of iteration

$iter$: current iteration number

w_{max} : maximum inertia weight

w_{min} : minimum inertia weight

From experience, it is known that:

1. When the best fitness is low at the end of the run in the optimization of a minimum function, low inertia weight and high learning factors are often preferred.
2. When the best fitness is stuck at one value for a long time, number of generations for unchanged best fitness is large. The system is often stuck at a local minimum, so the system should probably concentrate on exploiting rather than exploring. That is, the inertia weight should be increased and learning factors should be decreased. Based on this kind of knowledge, a fuzzy system is developed to adjust the inertia weight, and learning factors with best fitness (BF) and number of generations for unchanged best fitness (NU) as the input variables, and the inertia weight (*w*) and learning factors (c_1 and c_2) as output variables.

The BF measures the performance of the best candidate solution found so far. Different optimization problems have different ranges of BF value. To design a FAPSO applicable to a wide range of problems, the ranges of BF and NU are normalized into [0, 1.0]. To convert BF to a normalized BF format, equation 15 is used:

$$NBF = \frac{(BF - BF_{min})}{(BF_{max} - BF_{min})} \tag{15}$$

Where $BF_{min}$is the real minimum fitness value and BF_{max} is greater than the maximum fitness value. NU can be converted into [0, 1.0] in similar way. The value for *w* is bounded in $0.2 \leq w \leq 1.2$ and the values of $c_1$and c_2 are bounded in $1.0 \leq c_1, c_2 \leq 2.0$.

In the fuzzy adaptive particle swarm optimization, each control variables vector or particle was evaluated according to the following algorithm:

Step (1) Input the power system data and the FAPSO parameter limits.

Step (2) Generate the initial searching points and velocities of particles randomly and uniformly in the searching space. For each particle, calculate objective functions.

Step (3) Set each initial searching point to p-best; the initial best evaluated value among p-best is set to g-best.

Step (4) Update the FAPSO control parameters (*w*, c_1 and c_2).

Step (5) New velocities and searching points are calculated using 12 and 13.

Step (6) Evaluate all the particles in the new position. That is to calculate objective functions.

Step (7) If the evaluation value of each particle is better than the previous p-best, the value is set to p-best; if the best p-bestis better than g-best, the value is set to g-best. All of g-bests are stored as candidates for the final solution.

Step (8) Check the stop criterion, usually a sufficiently good fitness value or a maximum number of iteration. If the stop criterion is not satisfied, then continue the process by returning to step 4. Otherwise, proceed to next step.

The model of FAPSO can be described as follows:

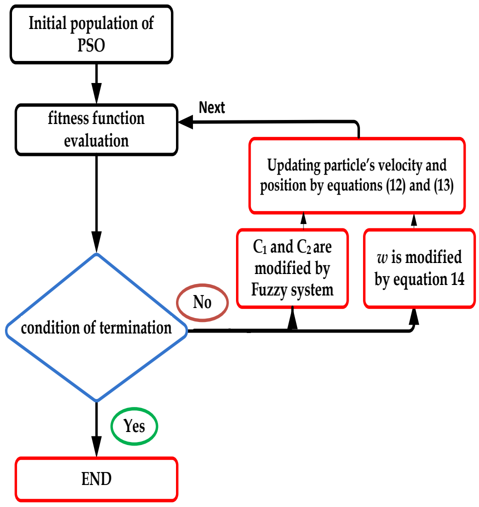

Figure 2. Flow Chart of the Fuzzy Adaptive Particle Swarm Optimization Technique

The membership function of inputs and outputs of FAPSO model is shown below:

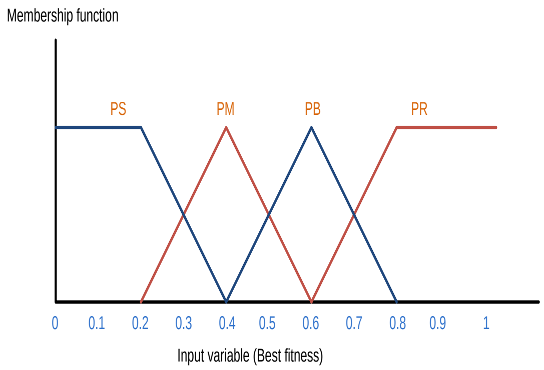

Figure 3. Membership function of Best fitness BF

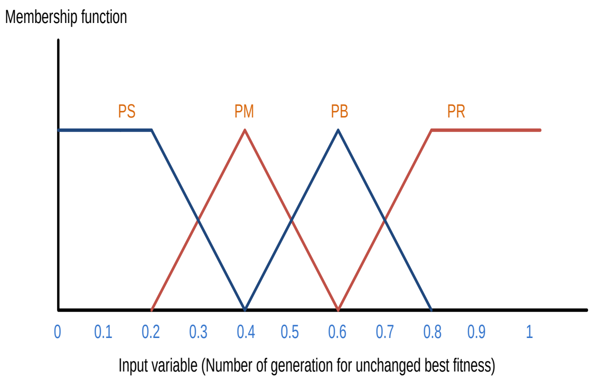

Figure 4. Membership function of number of generations for unchanged best fitness NU

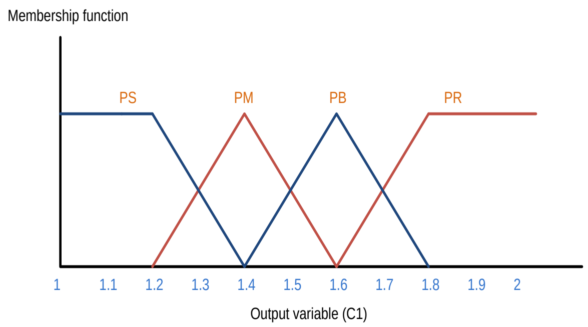

Figure 5. Membership function for learning factor c_1

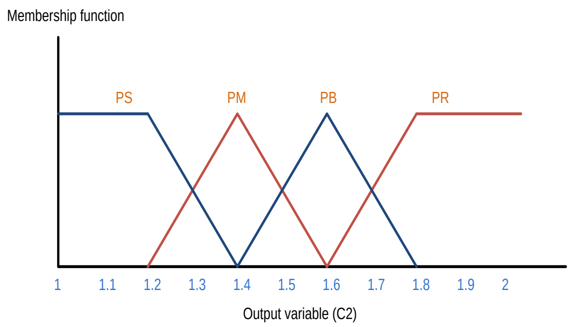

Figure 6. Membership function for learning factor c_2

The fuzzy system consists of four principal components: fuzzification, fuzzy rules, fuzzy reasoning and defuzzification, which are described as following:

Fuzzification

Among a set of membership functions, left-triangle, triangle and right-triangle membership functions are used for every adjusted input and output as illustrated in Figure 3, Figure 4, Figure 5, and Figure 6. Four membership function were used in this work PS (positive small), PM (positive medium), PB (positive big) and PR (positive bigger) are the linguist variables for the inputs and outputs.

Fuzzy Rules

The Mamdani-type fuzzy rule is used to formulate the conditional statements that comprise fuzzy logic. The fuzzy rules in Table 4 are used to adjust the learning factors c_1 and c_2. Each rule represents a mapping from the input space to the output space.

Table 4. Fuzzy rules for social and cognitive parameters c_1 and c_2

C_1		NU			
		PS	PM	PB	PR
NBF	PS	PR	PB	PB	PM
	PM	PB	PM	PM	PS
	PB	PB	PM	PS	PS
	PR	PM	PM	PS	PS

C_2		NU			
		PS	PM	PB	PR
NBF	PS	PR	PB	PM	PM
	PM	PB	PM	PS	PS
	PB	PM	PM	PS	PS
	PR	PM	PS	PS	PS

Fuzzy Reasoning

The fuzzy control strategy is used to map from the given inputs to the outputs. Mamdani's fuzzy inference method is used in this paper [19]. The AND operator is typically used to combine the membership values for each fired rule to generate the membership values for the fuzzy sets of output variables in the consequent part of the rule. Since there may be several rules fired in the rule sets, for some fuzzy sets of the output variables there may be different membership values obtained from different fired rules. These output fuzzy sets are then aggregated into a single output fuzzy set by OR operator. That is to take the maximum value as the membership value of that fuzzy set.

Defuzzification

To obtain a deterministic control action, a defuzzification strategy is required. The method of centroid (center-of-sums) is used as shown below:

$$y = \frac{\int_y \sum_{i=1}^{n} y.\mu_{Bi}(y)dy}{\int_y \sum_{i=1}^{n} \mu_{Bi}(y)dy} \tag{16}$$

Defuzzified value is directly acceptable values of C_1 and C_2 parameters, where the input for the defuzzification process is a fuzzy set $\mu_{Bi}(y)$ (the aggregate output fuzzy set) and the output is a single number y.

5. Simulation Results

The simulation and calculations are implemented using the Matlab programming language and executed on a PC with a Pentium IV, Intel Core 2 Due 2.26 G CPU. The results obtained are given below.

5.1 The System Voltage Profile

The system voltage profile obtained by optimal economic dispatch and fuzzy adaptive particle swarm optimization meet the main objective criterion and these values are depicted in Figure 7.

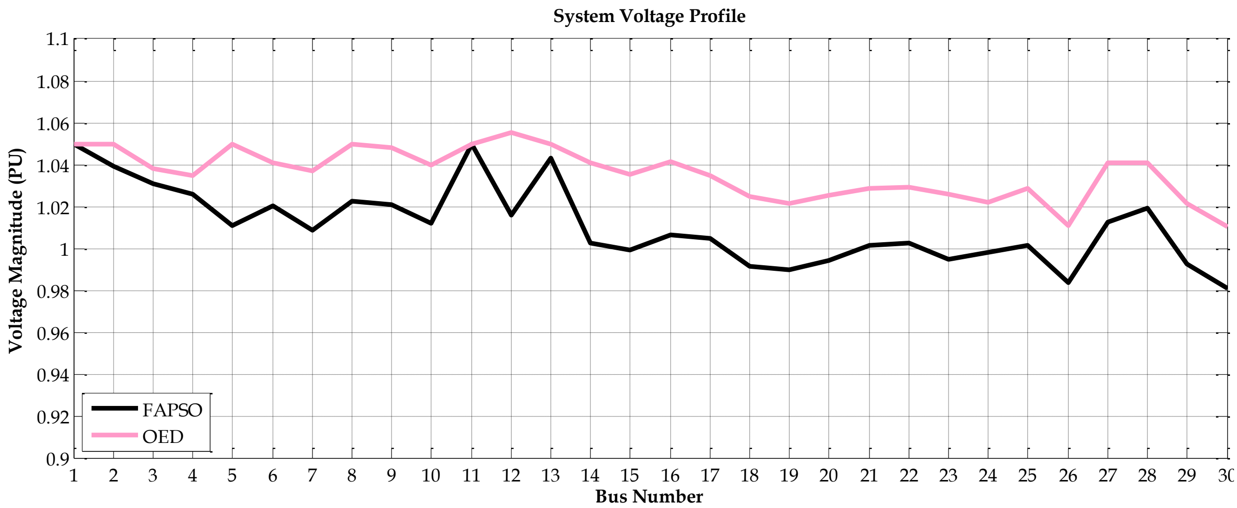

Figure 7. The System Voltage Profile obtained by the OED and FAPSO

It should be noted that, the minimum value of the voltage at the system buses obtained by Optimal Economic Dispatch is 1.022 πυ while it is equal to 0.981πυfor Fuzzy Adaptive Particle Swarm Optimization, and the maximum value is 1.056 pufor OED and 1.05 pu for FAPSO.

5.2 The Control Variables and Bus Data

After the run is complete the numerical values for the control variables and bus data are obtained by the Fuzzy Adaptive Particle Swarm Optimization. Table 5 shows the results at the system buses.

Table 5. The Bus Data Obtained by the Fuzzy Adaptive Particle Swarm Optimization

Bus no.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generation		Q_{min}	Q_{max}	Q_{sh}
				MW	Mvar	MW	Mvar			
1	1	1.050	0.000	0	0	150.42	-17.63	0	0	0
2	2	1.039	-3.358	21.7	12.7	42.05	25.32	-40	50	0
3	0	1.031	-5.031	2.4	1.2	0.00	0.00	0	0	0
4	0	1.026	-6.033	7.6	1.6	0.00	0.00	0	0	0
5	2	1.011	-9.298	94.2	19	18.89	22.83	-40	60	0
6	0	1.021	-7.086	0	0	0.00	0.00	0	0	0
7	0	1.009	-8.520	22.8	10.9	0.00	0.00	0	0	0
8	2	1.023	-7.423	30	30	10.00	37.32	-30	70	0
9	0	1.021	-8.550	0	0	0.00	0.00	0	0	0
10	0	1.012	-10.421	5.8	2	0.00	0.00	0	0	0
11	2	1.050	-6.549	0	0	30.00	14.89	-6	24	0
12	0	1.016	-9.089	11.2	7.5	0.00	0.00	0	0	0
13	2	1.043	-7.196	0	0	40.00	20.91	-6	40	0
14	0	1.003	-10.130	6.2	1.6	0.00	0.00	0	0	0
15	0	1.000	-10.357	8.2	2.5	0.00	0.00	0	0	0
16	0	1.007	-9.953	3.5	1.8	0.00	0.00	0	0	0
17	0	1.005	-10.505	9	5.8	0.00	0.00	0	0	0
18	0	0.991	-11.126	3.2	0.9	0.00	0.00	0	0	0
19	0	0.990	-11.377	9.5	3.4	0.00	0.00	0	0	0
20	0	0.995	-11.200	2.2	0.7	0.00	0.00	0	0	0
21	0	1.002	-10.945	17.5	11.2	0.00	0.00	0	0	0
22	0	1.003	-10.947	0	0	0.00	0.00	0	0	0
23	0	0.995	-11.058	3.2	1.6	0.00	0.00	0	0	0
24	0	0.998	-11.619	8.7	6.7	0.00	0.00	0	0	9.43
25	0	1.002	-11.619	0	0	0.00	0.00	0	0	0
26	0	0.984	-12.052	3.5	2.3	0.00	0.00	0	0	0
27	0	1.013	-11.343	0	0	0.00	0.00	0	0	0
28	0	1.019	-7.610	0	0	0.00	0.00	0	0	0
29	0	0.993	-12.599	2.4	0.9	0.00	0.00	0	0	0
30	0	0.981	-13.502	10.6	1.9	0.00	0.00	0	0	0

It is noted that the voltage magnitudes at system buses lie within the prescribed limits and all constraints are successfully satisfied. Table 6 below presents the control variables including positions of the four tap-changer-transformers for both Optimal Economic Dispatch and Fuzzy Adaptive Particle Swarm Optimization.

The voltage deviation for OED is 0.0325 pu while it is at 0.0109 pu for FAPSO with a reduction of 66.46%. The real power loss obtained by OED is 8.3703 MW while the FAPSO gave 7.8369 MW for these losses with a reduction of 6.38%. The runtime is 0.2383 seconds for OED and 14.1275 seconds for FAPSO. Table 6 summarizes these results.

Table 6. The Control Variables Obtained by the OED and FAPSO

Variable	$T_{6\text{-}9}$	$T_{6\text{-}10}$	$T_{4\text{-}12}$	$T_{28\text{-}27}$	*Voltage Deviation*	*% Voltage Deviation*	*Power Loss MW*	*% Power Loss*	*Elapsed Time (s)*
OED	0.9780	0.9690	0.9320	0.9680	0.0325	100	8.3703	100	0.2383
FAPSO	1.0099	0.9234	1.0254	0.9796	0.0109	33.54	7.8369	93.62	14.1275

The comparison shows clearly the superiority of the proposed technique over the traditional optimal economic dispatch method.

6. CONCLUSION

The proposed Fuzzy Adaptive Particle Swarm Optimization method for Voltage VAR Control considering voltage stability is applied to the IEEE 30-bus power system. The swarm size is taken as 50 and the number of iterations is set at 20. The inertia weight is linearly decreased from 0.95 to 0.7 according to linearly decreased equation while the learning factors are modified using fuzzy logic. The proposed technique was employed taking advantage of a variety of control tools such as transformer tap setting, static VAR compensations and voltage-control buses in order to solve the voltage-control problem. The voltage-control and reactive power dispatch problems were formulated as mathematical optimization problems subject to the applicable constraints. The inertia weight of the adaptive particle swarm was decreased linearly to explore the search space from local to global area while the fuzzy logic is used to modify the parameters of particle swarm, namely, the cognitive and the social parameters. No convergence problems were experienced when the FAPSO techniques is employed to the voltage-control problem. This means there is a solution every time the program is run. Every solution obtained depends on the initialization of the parameters of the swarm.

The best result is then recorded and taken as the optimum solution. The solution obtained gave acceptable results as far as the voltage magnitudes at the system buses are concerned. The new technique provides better voltage deviation with more than 66 percent reduction than the optimal economic dispatch. In addition, the real power loss obtained using the new method is less by more than 6 percent of that of the optimal economic dispatch. Thus, suitable selection of the particle swarm parameters has led to better voltage deviation and less real power loss. The IEEE-30-bus system has been used to conduct this research because it has a reasonable number of buses of all kinds and transmission lines. In addition all kind of voltage-control tools are available and can be employed to serve the main objective of this paper. It is also strongly believed that the proposed technique could be employed to other power system models with various sizes.

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